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# Potential variation in opportunity cost estimates for REDD+ and its causes

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ABSTRACT

REDD+ programs and projects aim to mitigate climate change by reducing deforestation and forest degradation and enhancing forest carbon stocks. The viability of REDD+ programs depends in a large part on their opportunity costs (OCs); however, large variation exists in the estimated OC. This study aims to quantify the variation in OC reported in the literature and identify its causes. In addition to a careful description, a meta-analysis was conducted to examine the heterogeneities across the different estimating methods, data sources, deforestation drivers, and geographic regions found in previous studies. Our results show a large variation in the estimated OC because of differences in data sources, assumptions about future markets, and factors, such as carbon density, crop price and yield, and time horizon. Furthermore, variation exists even among studies of the same driver(s) of deforestation and forest degradation, within the same continent, and from the same data source. Time horizon is the largest contributor to cost variation, followed by carbon density and crop price. Geographically, the OCs are \$19.49/t$CO_2$e in Africa, \$9.19/t$CO_2$e in Asia Pacific, and \$4.33/t$CO_2$e in Latin America, respectively. Despite their large variation, the REDD+ OCs remain fairly low in most reasonable cases.

## 1. Introduction

Greenhouse gases (GHGs) have contributed to a global mean surface warming between 0.5 °C and 1.3 °C over the period of 1951–2010 (IPCC, 2013a), and carbon dioxide ($CO_2$) is the primary contributor. The average annual increase in global $CO_2$ concentration was 1.7 ppm $yr^{-1}$ from 1980 to 2011 (IPCC, 2013b). Following energy consumption, deforestation and forest degradation is the second most common greenhouse gas emitter, with 17% of the global anthropogenic $CO_2$ emissions (FAO, 2011; Kremen et al., 2000; IPCC, 2007). Reducing emissions from deforestation and forest degradation, along with conserving and enhancing forest carbon stocks and implementing sustainable forest management, or REDD+, thus quickly became recognized as an important strategy for mitigating climate change by the United Nations Framework Convention on Climate Change, or UNFCCC. Currently, 64 countries have been involved in REDD+ piloting, readiness, and/or formal-implementation projects (UN-REDD, 2018).

REDD+ has been generally viewed as an economically competitive option for alleviating climate change, compared with many other projects, such as renewable energy use and energy efficiency improvement programs (IPCC, 2014; Pistorius, 2012; Stern, 2007). However, this cost-effectiveness consensus has been challenged and criticized, partly for being exceedingly optimistic by focusing on the opportunity cost alone and for not considering the associated implementation and transaction costs (Fosci, 2013; Dang Phan et al., 2014). Opportunity cost is considered a major component in the total cost of avoiding deforestation (Rakatama et al., 2017), and it refers to the foregone benefits deriving from stopping conversion of forestland to other land covers in the course of REDD+ implementation. Extensive empirical studies have focused on the OCs of avoiding forest conversion (Osborne and Kiker, 2005; Blaser and Robledo, 2007; Kindermann et al., 2008; Sandker et al., 2009; Plumb et al., 2012; Borrego and Skutsch, 2014; Thompson et al., 2017).

Indeed, OCs are fairly low in most cases, especially from the earlier estimations (Bellassen and Gitz, 2008; Börner and Wunder, 2008). For example, Potvin et al. (2008) find that the opportunity cost of REDD+ in Panama is \$1.23/t$CO_2$e. Similarly, applying a general equilibrium model, Warr and Yusuf (2011) estimate the opportunity cost of REDD+ in Indonesia to be \$1.04/t$CO_2$e. However, some later studies report that the OCs of REDD+ can be high (Nuru et al., 2014; Borrego and Skutsch, 2014). For instance, Tilahun et al. (2016) reveal that the OCs in Ghana range from \$6.5/t$CO_2$e to \$24/t$CO_2$e, and Fisher et al. (2011a) show that the OCs in Malaysia range from \$46/t$CO_2$e to \$48/t$CO_2$e. Clearly, these large variations in the OCs render the role of REDD+ in mitigating climate change less certain and less attractive, but more controversial. The current study aims to assess the degree of heterogeneity

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in OCs of REDD + and the major factors affecting the OCs using micro-level data and a meta-regression.

To be sure, qualitative approaches and quantitative methods have been employed in analyzing the cost heterogeneity; the empirical results have shown the costs of carbon offsets through forestry varying widely over space and time (Sedjo et al., 1995; White and Minang, 2011; Dang Phan et al., 2014; Rakatama et al., 2017). In a recent literature review, Rakatama et al. (2017) also note that the wide range in OC estimates is affected by study location and scale, and the variation in costs across regions is due to alternative land uses. In other words, different socioeconomic and forest conditions across regions, coupled with differences in alternative land uses, approaches, scales, and locations, can result in variation in the estimated OCs as well as benefits (Fearnside, 2002; Boucher, 2008; Mbatu, 2016; Ickowitz et al., 2017; Wang et al., 2018).

Previous studies have also attempted to investigate the causes of the cost variation using regression models. Based on their earlier work (van Kooten et al., 2004), van Kooten et al. (2009) find that the location of the forestry activities and programs play a significant role in the estimated carbon offset costs. Similarly, Dang Phan et al. (2014) combine "internal factors" with "external factors" in their study and conclude that the method, discount rate, and carbon density can influence the "unit costs." These findings have advanced our understanding of the sources of costs variation; meanwhile, it seems that some of the studies have ignored certain important factors affecting the magnitudes of the opportunity costs. As a matter of fact, some contradicting results regarding the discount rate and soil carbon variables have emerged from the literature.

Consequently, the REDD + potentials are only partially understood, and this lack of understanding is not conducive to proper project design and evaluation (Borrego and Skutsch, 2014; Irawan et al., 2013). Estimating the REDD + OCs entails collecting the appropriate data and choosing the appropriate method(s) for identifying the benefits of the most likely alternative(s) of forestland use. Different land uses generate different economic returns, and local people are often assumed to seek the largest possible returns. Therefore, we have conducted a careful literature analysis to assess the variability of the REDD + OCs and the factors that influence the variation by integrating qualitative and quantitative approaches and using multi-level data and meta-regression.

We hope that our analysis will contribute to a more complete and deeper understanding of the variability of REDD + OCs, which should in turn help policy makers, business leaders, and community organizations to solidify their participation in forest-based climate mitigation efforts. In Section 2, we outline the methods of our literature search and analysis, and our data extraction (more detailed information can be found in the Appendix). In Section 3, we present our descriptive results, identifying differences in data sources, estimating methods, drivers of deforestation, and the countries covered by the previous studies. In Section 4, we report our findings. Finally, Section 5 contains conclusions and discussions.

## 2. Search method

We conducted an online literature search of the databases of the Science Citation Index Expanded and Social Sciences Citation Index provided by Web of Science. The original information was gathered by searching the following keywords: "opportunity cost," "REDD," "cost," "deforestation," and "degradation." Thirty-three studies were identified. We then excluded the articles that did not estimate OCs empirically and/or those that merely considered the costs conceptually.

Altogether, 26 articles were selected. On average, each study has about eight observations because of the alternative scenarios and assumptions considered, regarding discount rate, time horizon, and land use, among others (Table 1). So, a total of 227 observations were gathered from the 26 studies. The largest number of observations coming from a single study was 34 (Borrego and Skutsch, 2014), while three studies had only one observation (Potvin et al., 2008; Yamamoto and Takeuchi, 2012; Nuru et al., 2014). As suggested by Stanley (2001), the mean value was chosen as a proxy for the multiple cost observations in each study. To make the results of the selected studies comparable, estimates were adjusted to dollar values of 2010 based on the US CPI. The resulting OCs in $/tC were then divided by the molecular weight conversion factor (3.67) to derive the counterpart in $/tCO$_2$e (GOFC-GOLD, 2009).

The OCs of REDD + range from $0.3/tCO$_2$e to $2027/tCO$_2$e in the selected studies; the average cost is $13/tCO$_2$e if the extreme value of $2027/tCO$_2$e is excluded. Six studies from Africa have focused on three countries; likewise, six studies from Latin America have covered five countries, and nine studies from Asia have included four countries. The remaining five studies have provided multi-continental cost estimates of avoided deforestation; hence, we lumped them into the group labeled "global."

Further, differences in discount rate, carbon density, and time horizon have produced significantly different results (Dang Phan et al., 2014; van Kooten et al., 2004; van Kooten et al., 2009). Thus, we chose the discount rate, crop (forest products) price and yield, carbon density, and time horizon as the potential determinants (See Table 2). For discounting, the most commonly used rate in the studies is 10% per year. The price and output refer to the agricultural (forest) product unit price and average yield. The data for price and yield were directly obtained from original studies if these data were available; otherwise, they were calculated from the FAO database. Carbon density measures the amount of carbon per hectare and thus is used in estimating the economic benefits. The time horizon is the project time span used in each study, varying from 5 to 30 years. Many have considered different land uses, resulting in various OC estimates (Borrego and Skutsch, 2014; Fisher et al., 2011a; Irawan et al., 2013; Graham et al., 2017).

## 3. Descriptive results

As noted, the data sources, analytic methods, and concrete drivers of deforestation and forest degradation directly affect the estimates of REDD + OCs. A careful examination of these and other facts is thus needed before investigating the determinants to identify the particular sources of variation.

### 3.1. Data and methods

The data sources for estimating REDD + OCs can be categorized as "bottom-up" and "top-down," respectively, depending on whether they come from survey information or official statistics (Fischer et al., 2016; Thompson et al., 2017; White and Minang, 2011). Among the selected studies, the proportion of studies that adopt survey information accounts for 35%, with the remaining 65% are based on official statistics. Most national level and sub-national level studies use survey data, while other national-level studies and the continental ones use official statistics. Survey includes household questionnaire and company interview. A survey mainly obtains what the alternative land uses, corresponding yields and market prices of the projected outputs are; this type of work may also include information on the willingness to accept compensation and the range of potential compensation for the OCs. Official statistics may include findings on carbon emissions and economic outputs from macro sources. The difference between the two approaches is partially reflected in their accuracies. Survey information can represent the real conditions of farmers and local market, and appears to be able to capture the economic and social contexts of study regions. By contrast, official statistics at the macro-level may neglect variations among local entities and thus deliver only an overall average value.

The Net Present Value (NPV) model and its variant represent most widely used methods for estimating OCs, but other models are also

**Table 1**
Selected studies of OCs.

| Continent | Country | Study | Observations | Mean OC[a] (Range)[b] |
|---|---|---|---|---|
| Africa | Cameroon | Thompson et al. (2017) | 4 | 2026.50 (7.74–5371.99) |
| | | Bellassen and Gitz (2008) | 3 | 3.19 (2.70–3.68) |
| | Ghana | Sandker et al. (2009) | 4 | 66.30 (56.10–76.5) |
| | | Tilahun et al. (2016) | 16 | 9.35 (0.21–22.91) |
| | Tanzania | Fisher et al. (2011b) | 3 | 3.90 (3.20–5.50) |
| | | Nuru et al. (2014) | 1 | 21.84 |
| Latin America | Brazil[d] | Nepstad et al. (2007) | 6 | 1.15 (0.45–1.73) |
| | | Börner and Wunder (2008) | 6 | 1.98 (0.68–3.64) |
| | Guyana | Osborne and Kiker (2005) | 16 | 0.28 (0.05–0.38) |
| | Honduras | Plumb et al. (2012) | 6 | 1.73 (2.34–6.02) |
| | Mexico | Borrego and Skutsch (2014) | 34 | 16.90 (8.47–42.33) |
| | Panama | Potvin et al. (2008) | 1 | 1.23 |
| Asia Pacific | Indonesia | Cacho et al. (2014) | 22 | 4.85 (0–9.71) |
| | | Warr and Yusuf (2011) | 10 | 1.04 (0.90–1.24) |
| | | Irawan et al. (2013) | 15 | 31.42 (0.58–172.82) |
| | | Graham et al. (2017) | 2 | 17.65 (15.36–19.93) |
| | | Yamamoto and Takeuchi (2012) | 1 | 4.68 |
| | Malaysia | Fisher et al. (2011a) | 2 | 38.76 (28.56–48.96) |
| | Nepal | Prakash Joshi et al. (2016) | 2 | 54.17 (46.45–51.38) |
| | | Pandey et al. (2017) | 4 | 0.97 (0.08–2.02) |
| | Vietnam | Ogonowski and Enright (2013) | 8 | 9.19 (1.36–18.45) |
| Global | | Ickowitz et al. (2017) | 17 | 24.00 (1.86–257.19) |
| | | Kindermann et al. (2008) | 24 | 10.60 (1.09–40.06) |
| | | Sathaye et al. (2011) | 8 | 0.86 (0.45–3.07) |
| | | Blaser and Robledo (2007) | 6 | 3.01 (0.46–7.69) |
| | | Overmars et al. (2014) | 6 | 16.96 (0–64.52) |
| Aggregate | | | 227 | |
| Average | | | 8.73 | 91.25<br>13.31[c] |

[a] The unit is \$/t $CO_2$e (2010 dollars).
[b] When only one observation was present in the study, the range of values was not listed.
[c] The extreme value was excluded from calculating the mean value.
[d] Although Brazil has not participated in the REDD+ program, some studies have shown an ex-ante assessment of the OC.

applied for cost estimation. Table 3 below summarizes the methods used in the previous studies. The NPV model estimates the total net revenue, which is the amount of discounted net benefits over a certain period of time (say, *T* years). One variant of the NPV model is its equivalent annuity, which converts the NPV figure into average annual net income. Part of the difference between the two involves the former giving an aggregate value, which enables farmers and policymakers to know the full OC. On the contrary, the latter allows farmers to understand how much their loss would amount to in the form of "annual income" over the next *T* years. Most of the previous studies are based on NPV, with only a few using annuities (Borrego and Skutsch, 2014; Pandey et al., 2017; Plumb et al., 2012).

### 3.2. Drivers of deforestation and forest degradation

The UNFCCC negotiations have urged countries to identify concrete drivers of deforestation and forest degradation; thus, forest depletion is not only reflected in the area and stock volume changes but also traced to the concrete causes (UNFCCC, 2010; IPCC, 2014; Hosonuma et al., 2012). Examining the drivers of deforestation and forest degradation is

**Table 2**
Variables, descriptions, and means ($n$ = 227).

| Variable | Description | Unit | Mean ± SD | Range |
|---|---|---|---|---|
| *Dependent variable* | | | | |
| Opportunity cost | Opportunity cost of REDD+ | US\$/t$CO_2$e | 91.25 ± 395.08 | 0–2026.50 |
| *Independent variables* | | | | |
| Discount rate | Discount rates are projected to value monetary benefits less than they currently do; this parameter is used to estimate the NPV herein | % | 7.00 ± 5.29 | 0–20 |
| Price | Price for a unit crop | US\$/kg | 0.91 ± 1.24 | 0.05–5.96 |
| Yield | Crop output for a unit land area | t/ha/year | 7.55 ± 5.08 | 0.29–16.92 |
| Carbon density | Often refers to the carbon stock change between two alternative land uses herein | tC/ha | 126.68 ± 86.13 | 1.82–236.45 |
| Time horizon | An x-year time horizon is utilized with the assumption that REDD+ will be implemented for x years | Years | 26.64 ± 18.97 | 8–100 |
| Data sources | | | | |
| Direct | Data from field survey | Dummy | 0.35 ± 0.49 | 0–1 |
| Secondary | Data from literature or official website | Dummy | 0.65 ± 0.49 | 0–1 |
| Drivers of deforestation | | | | |
| Agriculture | Foregone benefits from crops and livestock | Dummy | 0.42 ± 0.50 | 0–1 |
| Forest products | Foregone benefits from forest-based activities | Dummy | 0.08 ± 0.27 | 0–1 |
| Multiple | Foregone benefits from agriculture and forest products | Dummy | 0.50 ± 0.51 | 0–1 |
| Estimating methods | | | | |
| Average method | Dividing NPV by carbon density | Dummy | 0.77 ± 0.43 | 0–1 |
| Model | Global models or country-specific models. | Dummy | 0.23 ± 0.43 | 0–1 |
| Belowground carbon | Belowground carbon is considered in estimated value | Dummy | 0.40 ± 0.49 | 0–1 |

**Table 3**
Methods for estimating OCs.

| Methods | Types | Formulas | Descriptions |
|---|---|---|---|
| NPV method | Aggregate | (1) $\mathrm{NPV(T)} = \sum_t \left[\sum_j y_{j,t} p_{j,t} - \sum_i x_{i,t} c_{i,t}\right](1+r)^{-r}$ $NPV(T) = \Sigma t\,[\Sigma jyj, tpj - \Sigma ixi, tci](1+r) - t$ | $NPV(T)$ is the net present value calculated over $T$ years; $y_{j,t}$ is the yield of output $j$ in year $t$; $p_j$ is the price per unit of output; $x_{i,t}$ is the amount of input $i$ used in year $t$; $c_i$ is the cost per unit of input; and $r$ is the discount rate. |
| | | (2) $C_E = C_F - C_C$ | $C_C$ and $C_F$ are the stocks of carbon of the current land uses and forest lands; and $C_E$ is carbon emissions produced in the land-use conversion. (Carbon stocks include carbon in trees and soils.) |
| | | (3) $OC_1 = \frac{NPV(T)}{C_E(T)}$ | $OC_1$ is the opportunity cost over $T$ years. |
| | Annual | (1) $k = \frac{NPV\,[r(1+r)^T]}{(1+r)^T - 1}$ | $k$ is the equivalent annual annuity. |
| | | (2) $OC_2 = \frac{k}{C_E}$ | $OC_2$ is the annual opportunity costs during $T$ years; $C_E$ is the average carbon emissions among $T$ years. |
| Models | LEITAP (computable general equilibrium economic model) and IMAGE (the integrated, biophysical model) | | Source: Overmars et al. (2014) |
| | GTM (Global Timber Model) | | Source: Kindermann et al. (2008) |
| | GCOMAP (Generalized Comprehensive Mitigation Assessment Process Model) | | |
| | DIMA (Dynamic Integrated Model of Forestry and Alternative Land Use) | | |
| | INDONESIA E3-L (Economy-Equity-Environment-Land Model) | | Source: Warr and Yusuf (2011) |

thus worthwhile, leading to potentially very different REDD+ OCs (Cacho et al., 2014; Fisher et al., 2011b; Ogonowski and Enright, 2013).

Our discussion on the drivers here is based on information extracted from the original literature. Included in the drivers of deforestation and forest degradation are direct and indirect ones—the former refers to specific forest use or exploitation activity and the latter refers to other more fundamental cultural, institutional, and policy causes (Kissinger et al., 2012). The drivers vary with different stages of economic growth and different regions (Cropper and Griffiths, 1994; Houghton, 2012). Together, 44% of the reviewed studies estimated OCs from agriculture, which covers various crops and grazing activities. Meanwhile, about 8% of the studies estimated timber and non-timber forest product benefits, including commercial and non-commercial forest-based activities. The remaining studies (48%) provided cost estimates for combined agricultural and forestry activities.

Agriculture plays a significant role in driving deforestation. In the early development stage, the expansion of agricultural land leads to widespread forest destruction; farmers produce agricultural products to meet their own subsistence needs, and agriculture is the main source of livelihood during this stage (Leblois et al., 2017; Hosonuma et al., 2012; Gibbs et al., 2010). Globally, 80% of deforestation is due to agricultural production (FAO, 2015; Leblois et al., 2017). With improved technology and rising GDP, commercial agriculture may lead to more serious forest destruction (Angelsen and Kaimowitz, 1999). As an example, over 80% of the global demand for palm oil is supplied from Southeast Asia, which has caused extensive deforestation (Leblois et al., 2017; Geist and Lambin, 2002; Koh and Wilcove, 2007). Timber extraction and logging also result in forest degradation as well. Based on global data, Hosonuma et al. (2012) find that timber extraction accounts for 52% of forest degradation, firewood collection and charcoal production for 31%, fires for 9%, and livestock grazing for 7%. However, the shares of these activities vary from region to region, with timber harvesting exceeding 70% of the drivers of forest degradation in Latin America and Asia, and fuelwood and charcoal collection corresponding to 48% of those in Africa (Kissinger et al., 2012).

### 3.3. Countries

Included in the selected studies are 12 countries, accounting for 19% of those implementing various kinds of REDD+ projects. These countries differ in their economic development and forest resources, which affect the estimates of OCs. Other than national-level studies, continental- and sub-national level works have also been conducted to estimate OCs.

The OC estimates at the continental level include Asia, Africa, and Latin America, considering the impacts of implementing REDD+ projects on the global prices and outputs of agro-forestry products and the perceived "leakage" problem (Overmars et al., 2014; Kindermann et al., 2008; Sathaye et al., 2011). The national-level estimates are done for a particular country, which may neglect the impact of implementing the program on other countries (Fisher et al., 2011b; Börner and Wunder, 2008). However, most studies focus on estimates of subnational- and/or local-level OCs that account for factors such as household production activities, income levels, family composition, and education, which can exert different influences on the livelihood of farmers in different regions (Ickowitz et al., 2017; Cacho et al., 2014; Kindermann et al., 2008).

## 4. Statistical results

Recall that four studies were excluded: as a result, there were 220 observations when we applied forest plot and subgroup analysis to examine the degree of cost heterogeneity between studies and within groups. One of the reasons for exclusion was that the standard error per study was required but could not be calculated when only one observation was generated by a study. Another reason was that the missing details with the extreme value of \$2026/$tCO_2e$ in the figure. (See a discussion on the extreme value in section 5.) Dummy variables for drivers of deforestation, data sources, and belowground carbon were included in the regression.

### 4.1. Basic findings

The results of forest plot are presented in Fig. 1, which indicates that the REDD+ OCs range between 0 and \$97/$tCO_2e$, given 95% confidence intervalsDots in the plot represent the estimates of OCs in each study, with the horizontal line showing the 95% confidence interval and the dotted vertical line reflecting the overall result. The weights were based on the number of observations in each article with the assumption that a more accurate result was derived when more observations were included in a study. The brackets in the study ID are the countries involved in it.

Overall, $I^2 = 99.8\%$ ($p = .000$), which shows the presence of a high level of heterogeneity in the estimates from a statistical perspective. It can be seen that 99.8% of the inter-study heterogeneity came from true variation among studies, rather than sampling error. The maximum of

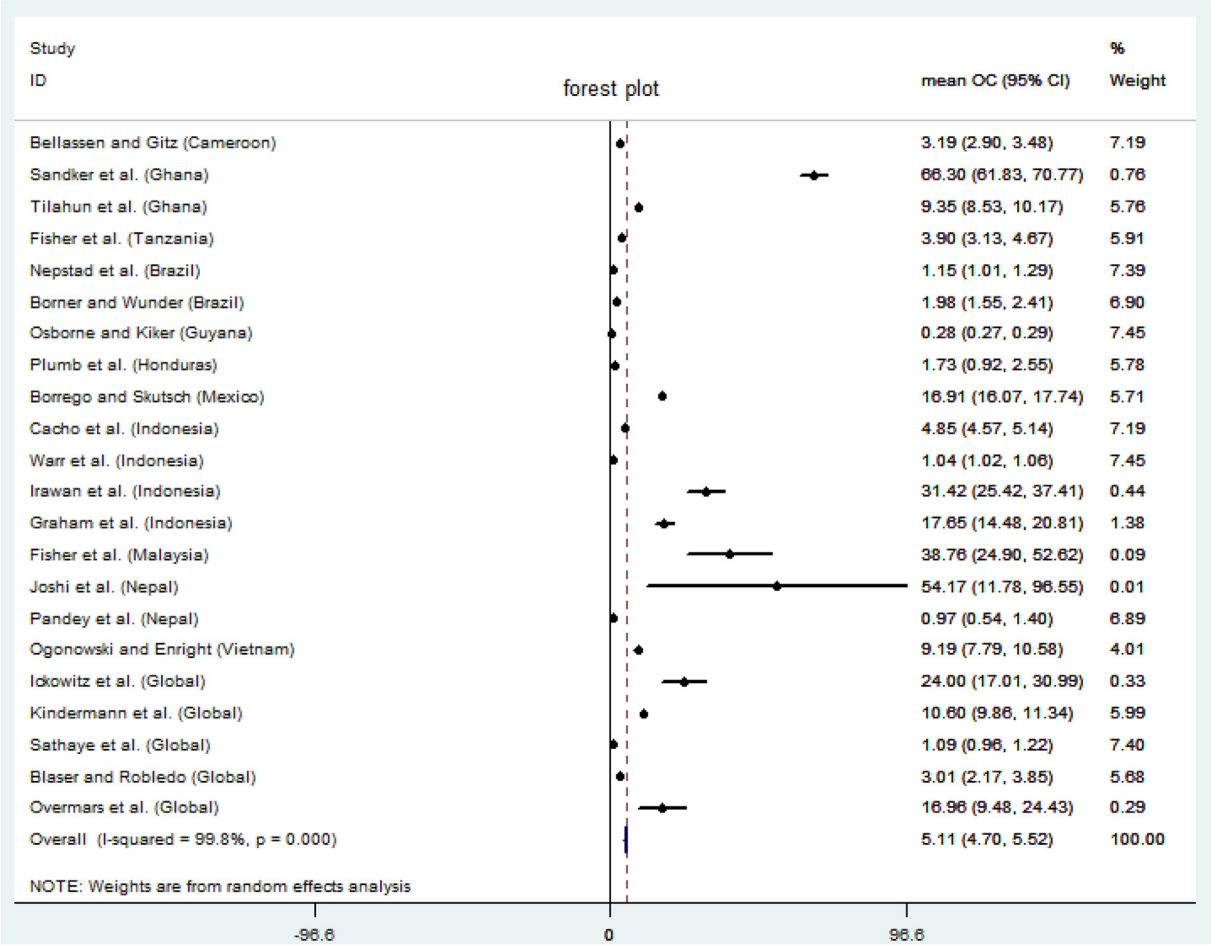

Study
ID
forest plot
mean OC (95% CI)
% Weight
Bellassen and Gitz (Cameroon) 3.19 (2.90, 3.48) 7.19
Sandker et al. (Ghana) 66.30 (61.83, 70.77) 0.76
Tilahun et al. (Ghana) 9.35 (8.53, 10.17) 5.76
Fisher et al. (Tanzania) 3.90 (3.13, 4.67) 5.91
Nepstad et al. (Brazil) 1.15 (1.01, 1.29) 7.39
Borner and Wunder (Brazil) 1.98 (1.55, 2.41) 6.90
Osborne and Kiker (Guyana) 0.28 (0.27, 0.29) 7.45
Plumb et al. (Honduras) 1.73 (0.92, 2.55) 5.78
Borrego and Skutsch (Mexico) 16.91 (16.07, 17.74) 5.71
Cacho et al. (Indonesia) 4.85 (4.57, 5.14) 7.19
Warr et al. (Indonesia) 1.04 (1.02, 1.06) 7.45
Irawan et al. (Indonesia) 31.42 (25.42, 37.41) 0.44
Graham et al. (Indonesia) 17.65 (14.48, 20.81) 1.38
Fisher et al. (Malaysia) 38.76 (24.90, 52.62) 0.09
Joshi et al. (Nepal) 54.17 (11.78, 96.55) 0.01
Pandey et al. (Nepal) 0.97 (0.54, 1.40) 6.89
Ogonowski and Enright (Vietnam) 9.19 (7.79, 10.58) 4.01
Idkowitz et al. (Global) 24.00 (17.01, 30.99) 0.33
Kindermann et al. (Global) 10.60 (9.86, 11.34) 5.99
Sathaye et al. (Global) 1.09 (0.96, 1.22) 7.40
Blaser and Robledo (Global) 3.01 (2.17, 3.85) 5.68
Overmars et al. (Global) 16.96 (9.48, 24.43) 0.29
Overall (I-squared = 99.8%, p = 0.000) 5.11 (4.70, 5.52) 100.00
NOTE: Weights are from random effects analysis
-96.6
0
96.6

**Fig. 1.** Forest plot of OCs (see Table 1 for data sources).

$66/tCO$_2$e was more than 235 times of the minimum of $0.28/tCO$_2$e. A total of 13 studies exhibited an OC less than $10/tCO$_2$e, five studies had an OC in the range of $10/tCO$_2$e-$25/tCO$_2$e, and four studies showed an OC over $30/tCO$_2$e. Small overlaps in 95% confidence level were also observed. This finding indicated the large variation in cost estimates. The weight of Joshi et al. (2016) was only 0.01%, and its 95% confidence interval may thus be inaccurate; hence, the overlaps with other studies should not be viewed as a basis for inferring no difference from other studies. The overall mean value of OC was $5.11/tCO$_2$e. Eleven studies attained estimates that exceed the overall mean value.

### 4.2. Disparities

The variation in OCs was further examined in terms of data sources, geographical scopes, and drivers of deforestation and forest degradation. Subgroup analysis can be used to test the variation in OC within each group. The results are shown in Table 4.

#### 4.2.1. Geographical scopes

The heterogeneity indexes $I^2$ of Africa, Asia Pacific, Latin America, and "global" exceed 99%, showing a massive variation among the individual studies for each continent. Meanwhile, the three continents account for 20%, 27%, and 33% of the all studies, respectively; and global-level studies account for 20% of the studies. The highest cost is up to $19.49/tCO$_2$e in Africa. The difference of cost estimates cannot be detected between the Asian and global studies, with $9.19/tCO$_2$e in Asia-Pacific and $9.76/tCO$_2$e globally. The lowest cost is $4.33/tCO$_2$e in Latin America.

#### 4.2.2. Data sources

The estimated $I^2$ of direct survey data and official statistics are 99.6% and 99.8%, respectively, indicating that the heterogeneity among the relevant studies remains high although the studies share the same data source. The OCs of two different data sources are $7.23/tCO$_2$e and $4.1/tCO$_2$e.

#### 4.2.3. Drivers of deforestation and forest degradation

Our analysis further illustrates that, even with the same driver, the OC estimates can be different. The average OC is $11/tCO$_2$e for forestland cleared for (commercial) agricultural production, $0.59/tCO$_2$e for giving up timber and fuelwood harvesting; $9.56/tCO$_2$e for combined (subsistence) agricultural production and forest harvesting. The difference in profits from alternative land uses results in diverse costs (Tilahun et al., 2016; Borrego and Skutsch, 2014). The heterogeneity in OCs derived from agricultural production, timber harvesting, and multiple drivers are 99.6%, 99.0%, and 99.6%, respectively.

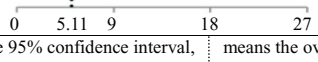
### 4.3. Meta-regression results

We obtained unstandardized and standardized coefficient results using Ordinary Least Squares (OLS) and Weighted Least Squares (WLS) models. Values in the first and third column show the original results of regression model. Values in the second and fourth column are measured in comparable units; as a result, all coefficients can be compared (Bring, 1994). The regression results are shown in Table 5.

The $R^2$ of WLS (80%) was larger than that of OLS (74%) (Table 5), which suggests that the weighted regression model can better explain the sources of difference in the OCs. A slight difference, mainly in the

**Table 4**
Results from subgroup analysis.

| Subgroup | Mean OC | 95% CI | Forest Plot | $I^2$ | Weights |
|---|---|---|---|---|---|
| Overall | 5.11 | 4.70-5.52 | | 0.998 | 100.00% |
| *Drivers* | | | | | |
| Agriculture | 11.01 | 8.83-13.19 | | 0.996 | 45.52% |
| Forest Products | 0.59 | -0.09-1.27 | | 0.900 | 14.34% |
| Multiple | 9.56 | 7.53-11.58 | | 0.996 | 40.14% |
| *Continent* | | | | | |
| Africa | 19.49 | 12.84-26.15 | | 0.997 | 19.62% |
| Asia Pacific | 9.19 | 7.79-10.58 | | 0.993 | 27.47% |
| Latin America | 4.33 | 2.58-6.07 | | 0.998 | 33.22% |
| Global | 9.76 | 4.77-14.76 | | 0.994 | 19.69% |
| *Data Source* | | | | | |
| Direct | 7.23 | 2.89-11.56 | | 0.996 | 31.33% |
| Secondary | 4.10 | 3.66-4.53 | | 0.998 | 68.67% |




*Note*: ◆ means the point estimates, —— means the 95% confidence interval, ⋮ means the overall opportunity cost.

price parameters, exists between the coefficients of the two models. In agricultural (forestry) products price and yield, carbon density, and time horizon, as well as the dummies of deforestation drivers and belowground carbon dummy, are significant at the 5% or 10% confidence level. This evidence indicates that these variables significantly explain the differences in the OCs among studies. The present study was unable to detect a significant influence of discount rate, data source, and method on cost estimates in meta-analysis. However, van Kooten et al. (2004) and Dang Phan et al. (2014) concluded that the discount rate parameter was negative.

Time horizon is the largest contributor to OC heterogeneity because its standardized coefficient exceeds that of any other variable. That parameter is then followed by carbon density, price, and yield. If the foregone benefits are from the agriculture sector, the costs would be less than that from forests (which are the baseline in models). Similarly, multiple incomes generate lower costs instead of forest activities. The inclusion of belowground carbon dummy produces significantly lower costs than those obtained when belowground carbon (which is the baseline in models) is excluded.

The positive impact of price on the OCs indicates that higher product prices result in more OCs when the forestland is cleared for other uses, increasing the cost ceteris paribus by US$240 based on OLS model. Yield also positively impacts OCs significantly at the 20% level. Contrary to the result of Dang Phan et al. (2014) and van Kooten et al. (2009), our result shows the effect of carbon density on the OC estimates is significantly positive, a 1% increase in the carbon density results in a US$4.3 increase in the cost.

In line with the result of Dang Phan et al. (2014), time horizon negatively affects OCs. In our study, a 1% increase in the time horizon results in a US$24 decrease in the opportunity cost, ceteris paribus. As argued by Sandker et al. (2009), as time goes by, soil fertility decreases, so the yield declines. Extrapolating the trend of the World Bank forecast for cocoa price in Ghana to 2020 results in a 40% decrease in 20 years; therefore, the OC in Ghana will likely decline. According to Fearnside (2002), the choice of time horizon usually affects the viability of avoiding deforestation projects. As shown in Table 5, extending the time horizon may encourage an additional number of developing countries to implement REDD+ projects, and reduce the OCs of countries, which are already in the process of avoiding deforestation and forest degradation. However, concluding that OC will decrease over time is unreliable. This issue is discussed in section 5.

## 5. Discussion

REDD+ has been generally viewed as a low-cost option to mitigate climate change compared with many other programs (Angelsen et al., 2012; Pistorius, 2012). However, OC, a major component of the total costs for avoided deforestation, could vary based on estimating methods, locations, scales, and alternative land uses (Rakatama et al., 2017). Based on 227 observations derived from 26 studies in the literature, this study has examined the degree of heterogeneity for OC estimates using forest plot and $I^2$ index and identified the main factors influencing the OCs using a meta-regression.

The variation in OCs is striking—the degree of heterogeneity for OC

**Table 5**
Meta-regression results.

| | *OLS* | | *WLS* | |
|---|---|---|---|---|
| Variables | Unstandardized coefficients | Standardized coefficients | Unstandardized coefficients | Standardized coefficients |
| Discount Rate | 5.4331 | 0.0713 | −3.7829 | −0.0495 |
| Price | 240.2919*** | 0.7400*** | 300.4929*** | 0.9253*** |
| Yield | 3.1774 | 0.0407 | 19.4176*** | 0.2454* |
| Carbon Density | 4.3263*** | 0.9242*** | 4.3416*** | 0.9271*** |
| Time Horizon | −24.1632*** | −1.1357*** | −26.6959*** | −1.2539*** |
| Direct data dummy | 179.1806 | 0.2187 | 87.9601 | 0.1096 |
| Average method dummy | −172.4353 | −0.1852 | −176.4415 | −0.1899 |
| Agriculture dummy | −1054.8350*** | −1.3219*** | −853.7113* | −1.0647* |
| Multiple incomes dummy | −1365.1990*** | −1.7221*** | −1230.3800*** | −1.5481*** |
| Belowground carbon dummy | −348.7252*** | −0.4250*** | −332.6633*** | −0.4037*** |
| $R^2$ | 0.7462 | 0.7459 | 0.8053 | 0.8052 |
| *F*-Statistic | 4.1160*** | 4.1095*** | 5.7903*** | 5.7859*** |

Note: Regression was based on 227 observations from 26 studies.
* Significant at 20% level or better.
** Significant at 10% level or better.
*** Significant at 5% level or better.

is more than 99%, which supports the view that costs are variable even if they are estimated according to the same data source, method, and land use. REDD + projects are widely implemented across Africa, Asia and Latin America. Different social and economic backgrounds exist over various regions. Geographically, the OCs are \$19.49/$tCO_2e$ in Africa, \$9.19/$tCO_2e$ in Asia Pacific, and \$4.33/$tCO_2e$ in Latin America, respectively. Globally, the mean OC is \$9.76/$tCO_2e$, consistent with that was observed by White and Minang (2011). These findings are partially in agreement with the results of Rakatama et al. (2017), other than the latter's estimate of \$14.11/$tCO_2e$ for Asia. In contrast, Kindermann et al. (2008), by employing three global models, find that the lowest-cost region is Africa, followed by Latin America and the globe, with the most expensive in Asia (as shown in Table 3). However, the distribution of costs across different regions is puzzling; as pointed out by Boucher (2008), the cost estimates of three continents are all similar (about \$2.3/$tCO_2e$).

Among the factors considered, time horizon holds the greatest impact on the OCs, followed by carbon density and price. Even though this study has clearly revealed the heterogeneity of REDD + OC, a few caveats must be articulated. First, our results show that carbon density would have a positive impact on the OC, which is different from the result of Dang Phan et al. (2014). Indeed, using carbon density to estimate the OC is ambiguous and inconsistent, because some studies use avoided carbon emissions as the basis for calculation (Tilahun et al., 2016; Fisher et al., 2011b) whereas others directly use the carbon contained in per hectare forestland for the same purpose (Ickowitz et al., 2017; Joshi et al., 2016). While the current results show that including belowground carbon can help decrease the OC, whether belowground carbon should be included in the calculation is unclear. Some reviews integrated the variable into the estimate, whereas others did not. Moreover, better production conditions such as soil and moisture, in areas abundant with forest resources of high carbon content than in those with low carbon content must be considered; the former conditions lead to higher crop yields, which would raise costs (Roudier et al., 2011; Edwards et al., 2014). Carbon density must be defined because it partly determines the cost estimates. Importantly, REDD + result-based incentives consider the achieved carbon reduction goals compared with reference emission level. Great uncertainty exists in belowground carbon (Ziegler et al., 2012), which needs to be validated with additional accurate data, when estimating an OC value.

Second, the extreme value of \$2026.5/$tCO_2e$ (Thompson et al., 2017) was generated by using the contingent valuation method, which infers OCs of REDD + by gauging the amount of compensation that farmers are willing to accept. The method incorporates the household characteristics, the yield and prices of crop, and the households' subjective judgment for land ownership and market crop price changes. Driven by self-interest, households often overestimate the OCs, which lead to an extreme value (Coursey et al., 1987; Hanemann, 1991). Other unusual OCs can be derived because agriculture plays a large role in development, and deforestation is the result of cultivation (Sandker et al., 2009; Irawan et al., 2013; Fisher et al., 2011a). The implementation of REDD + in areas with abundant forest resources and carbon content requires more compensation, because they cause additional emission reduction benefits. However, sufficient payments should also be given to such individuals because they lose more income and are less willing to abandon agricultural production on fertile soil than others. In these cases, countries need to develop their capacity to attract foreign and domestic investments, and encourage stakeholders to participate in the programs. For REDD + programs to become sustainable, the compensations should be sufficient to cover the OCs.

Finally, although the statistical coefficient of time horizon is negative, this result is insufficient to conclude that the cost of avoided deforestation would decrease over time. Most studies with the average cost method could not account for the time pattern of the benefits arising from changes in forest carbon stocks (Adams et al., 1999). In reality, the quality of forest stands often decreases over time because of the degradation from NTFP harvesting (Ogonowski and Enright, 2013). Averaged cost estimates do not effectively reflect the cost distribution over time; substantial misinformation exists in projecting future costs according to the averaged OCs.

In short, the OCs of REDD + are variably driven by different forces and considerations. Still, they remain fairly low in most reasonable cases (Boucher, 2008). This means that REDD + activities can be cost effective in most places. Of the empirical studies, 81% concluded that the estimates lie below the 2011 price for $CO_2$ of the European Union's Emission Trading Scheme (US\$24/$tCO_2e$), and only five studies showed estimates higher than \$30/$tCO_2e$. Future research should develop further nuanced and reliable estimates of the OC, as well as administrative and transaction costs; the added information is expected to form the basis for determining compensations for REDD + projects. Co-benefits (non-carbon benefits), such as biodiversity conservation, water regulation and cultural services have rarely been considered. Therefore, great uncertainties exist in the estimated OCs, and the debate over as well as discovery of REDD + OCs will continue.

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## Appendix A. Appendix

We integrated qualitative analysis and quantitative method in this study. First, we presented a descriptive analysis of the different methods and data sources in estimating the opportunity costs (OCs). This analysis provided descriptive results including data sources, estimating methods and alternative land uses, which were all key factors for OC estimates. Then, a statistical assessment was performed to examine the primary causes of OC variation.

We carried out a meta-analysis to quantify our findings on the variability of REDD + OCs and its determinants. Meta-analysis, as a statistical tool to quantitatively synthesize a large collection of results on the same phenomenon (Glass et al., 1981), has been widely applied in many fields (Nelson and Kennedy, 2009). Forest plot and three major indexes are often employed in meta analysis for determining whether true heterogeneity exists and to what level this heterogeneity extends. By observing the overlap of horizontal lines in a forest plot figure, the heterogeneity among results from multiple studies can be judged. It's impressive result may be less accurate than indexes. Multiple metrics are calculated in meta-analysis to enable researchers to understand the variation in outcomes of different studies and discover the factors influencing the variation. Among these metrics are $I^2$, $Q$, and $H$ statistics. $I^2$ and $H$ are based on the $Q$ statistic, but $I^2$ is more reasonable than $Q$ as a parameter after correcting for the degree of freedom (Higgins and Thompson, 2002; Huedomedina et al., 2006). Eqs. (1) and (2) are used to calculate for the $I^2$ index:

$$I^2 = (Q - df)/Q \times 100\% \quad (1)$$

$$Q = \Sigma w_i (T_i - T^*)^2 \quad (2)$$

where df is the degree of freedom of the studies (i.e., the total number of studies minus 1), $w_i$ is the weighting factor for the study $i$, $T_i$ is the effect value of the study $i$, and $T^*$ is the averaged effect value of all the studies. When conditional within-study homogeneous variances are assumed, then the $Q$ statistic exhibits a chi-square distribution with k-1 degrees of freedom. The $I^2$ index can be interpreted as a percentage of heterogeneity, that is, the part of total variation that is due to between-studies variance. $I^2$ is considered usually larger than zero; a positive relationship exists between $I^2$ value and the degree of heterogeneity among the studies (Higgins and Thompson, 2002). The between-studies variation are considered to be low, medium and high for the $I^2$ values of no more than 25%, 50%, and 75%, respectively (Huedomedina et al., 2006).

Meta-regression is considered to be an effective means to explain interstudy variation by identifying the factors. However, heteroscedasticity may occur in OLS regression because of different primary sample sizes, different sample observations, and varying estimation procedures (Cook and Weisberg, 1983; Knaub Jr., 2009; Rasheed et al., 2014). In this situation, WLS regression by using the reciprocal of the square root of each observed value as the weighting factor, is preferred (Nelson and Kennedy, 2009). Regression coefficients must be standardized when comparing variable coefficients in order to conclude each variable's contribution to the total heterogeneity. To provide standardized coefficients, scholars must first standardize all variables and then use these standardized variables to estimate by regression model (Bring, 1994).

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